Characterizing agricultural impacts of recent large-scale US droughts and changing technology and management

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ABSTRACT

Process-based agricultural models, applied in novel ways, can reproduce historical crop yield anomalies in the US, with median absolute deviation from observations of 6.7% at national-level and 11% at state-level. In seasons for which drought is the overriding factor, performance is further improved. Historical counterfactual scenarios for the 1988 and 2012 droughts show that changes in agricultural technologies and management have reduced system-level drought sensitivity in US maize production by about 25% in the intervening years. Finally, we estimate the economic costs of the two droughts in terms of insured and uninsured crop losses in each US county (for a total, adjusted for inflation, of $9 billion in 1988 and $21.6 billion in 2012). We compare these with cost estimates from the counterfactual scenarios and with crop indemnity data where available. Model-based measures are capable of accurately reproducing the direct agro-economic losses associated with extreme drought and can be used to characterize and compare events that occurred under very different conditions. This work suggests new approaches to modeling, monitoring, forecasting, and evaluating drought impacts on agriculture, as well as evaluating technological changes to inform adaptation strategies for future climate change and extreme events.

1. Introduction

Drought and heat events accounted for 12% of all billion-dollar US disasters from 1980 to 2011, but almost 25% of total monetary damages (FEMA, 1995; NCDC, 2012; Smith and Katz, 2013). The 1988 US drought is estimated to have cost the country $40 billion ($79 billion in 2013 dollars), behind only Hurricane Katrina in 2005 ($149 billion 2013 dollars) as the most costly US weather-related disaster (NCDC, 2012; Riebsame et al., 1991). Warming temperatures and shifting precipitation patterns may increase the frequency and severity of large-scale droughts in important agricultural regions (Sheffield and Wood, 2008; Solomon, 2007; Wehner et al., 2011). Recent work suggests that extended drought will harm more people in the future than any other climate-related impact, specifically in the area of food security (Romm, 2011).

Almost 40% (about $30 billion adjusted for inflation) of the cost of the 1988 drought is estimated to have come from direct losses to agricultural production (Smith and Katz, 2013). Preliminary estimates for the cost of the 2012 US drought based on direct crop losses alone are almost $30 billion (NCDC, 2012), and direct losses to livestock and dairy likely added another $5 billion. Once full direct and indirect estimates are available, 2012 is expected to rival or even surpass 1988 in terms of economic consequences.

For decades, agricultural scientists have developed models for evaluating the effects of weather on crops and productivity at the farm scale (e.g., DSSAT Jones et al., 2003, EPIC Williams et al., 1995, and APSIM McCown et al., 1996). These process-based models of crop growth and development can provide insight into the impacts of drought and other plant stressors (Porter and Semenov, 2005; Semenov and Porter, 1995). In the last decade, researchers have extended these tools to evaluate productivity at regional and global scales (Elliott et al., 2013, 2014b; Glotter et al., 2014; Izaurralde et al., 2006; Nelson et al.,

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2009) and applied them in multi-decadal multi-model assessments of climate change impacts (Rosenzweig et al., 2014). CERES-Maize (the primary maize model used in DSSAT and in this study) has been applied with two different ET estimation methods to reproduce the results of a field trial in Colorado. The model was found to be able to reproduce ET, grain yield, biomass, and soil moisture under various levels or irrigation in a semi-arid region (Anothai et al., 2013). At large scales, the effect of the number of rainy days in highly water limited settings has been considered in the context comparison of different gridded historical climate data products (Glotter et al., 2014). Large-scale extreme drought was recently evaluated using similar models and data to those used here, in the context of the possiblity of a new "Dust Bowl" type event in the early 21st century (Glotter and Elliott, 2016).

This study investigates (i) whether crop models can reproduce the observed impacts of past extreme events on agricultural production at various scales; (ii) to what extent they can reliably predict the impacts of forecasted or emerging meteorological events to improve lead times for response planning; (iii) to what extent changes in farm technology and management over decadal time-scales can affect system-level sensitivity to climate extremes; and (iv) how data and models can be used to improve assessments of the economic impacts of agricultural drought and comparisons of drought events separated by decades. US maize production over the last several decades provides the context for exploring these questions because of the meteorological intensity of recent droughts across the US Corn Belt states, documented technological and management changes in the sector over this period, and the quality and quantity of long time-series weather- and crop-related data.

2. Material and methods

2.1. Model assumptions and parameterizations

We simulate maize growth and yield using the field-scale CERES-Maize model, part of the Decision Support System for Agrotechnology Transfer (DSSAT Jones et al., 2003; Hoogenboom et al., 2010 for latest DSSAT release), at 10 km resolution for the conterminous US using the parallel System for Integrating Impact Models and Sectors (pSIMS Elliott et al., 2014b). The model is used in three distinct modes of study. To investigate our ability to reproduce past events, we performed hindcasts of 1979–2011 maize yields. To investigate our ability to predict the impacts of emerging meteorological events, we simulated 2012 US maize production before official statistics were released in February 2013 (Elliott et al., 2013). To investigate the effect of changes in agricultural technologies on the system-level drought sensitivity of commercial maize production, we analyzed the 1988 and 2012 droughts using historical counterfactuals (1988 weather with 2012 technology and practices, and vice versa). In all modes we evaluated the ability of the crop model system to reproduce observed drought impacts at various scales by comparing simulated yields with USDA NASS survey data at state and national levels. In so doing, we enhance understanding of the validity of climate change impact assessments based on dynamic process-based crop models (Rosenzweig et al., 2014).

Simulations for rainfed and irrigated maize were driven by weather data up to and including November 30, 2012, considering the following management practices and trends:

- **Planting date**: We simulated five distinct planting dates each year, the dates at which 10, 30, 50, 70 and 90% of the crop were reported to be planted based on state- and Crop Reporting District (CRD)-level crop progress data (National Agricultural Statistics Service, 1995-2013). These outputs were equally weighted in the aggregated results.
- **Relative maturity (RM) group**: To reflect the fact that seed-choice decisions are made based on local recent environmental conditions, the relative maturity (RM) group of the chosen cultivar is determined separately in each five-year period and for each planting

date. The decision is made by estimating the optimal RM over the preceding 5-year period using the local history of growing degree units accumulated between the planned planting and assumed maturity day.
- **Planting density**: Based on state level crop progress data from 1979 to 2012.

Simulations also include genetic yield improvement trends parameterized based on literature and on discussions with academic and industry experts in modeling and breeding:

- **Kernel number** was increased linearly by 9% over the simulation period from 1979 to 2012 (Echarte et al., 2013) and
- **Radiation use efficiency** was increased linearly by 10% over the simulation period. This increase was estimated through discussions with breeders and crop experts to represent the fact that more recent maize hybrids have stay-green characteristics (which increase late season dry matter accumulation, i.e. RUE) and also have more upright leaves allowing for higher plant population without reduced per-plant RUE (upright leaf angle would thus increase average RUE) (Tollenaar and Lee, 2006). CERES-Maize does not facilitate direct modeling of stay-green or upright leaf angle, so RUE increases were used to mimic these factors.

Finally we considered two land-use change adaptations in post processing (both calibrated with NASS data):

- Amount of **cultivated corn area** in each county from 1979 to 2012 and
- Fraction of that area that is **irrigated** vs. rainfed.

Simulations were run with input data at a variety of spatial and temporal scales including:

- Daily time-series of key weather variables spanning January 1, 1979 to November 30, 2012, from the North American Regional Reanalysis (Mesinger et al., 2006);
- Soil profile parameters (including most notably the average soil textures, bulk density, organic carbon content, and water holding characteristics at various depth layers along with the surface drainage and runoff characteristics) were estimated from the Harmonized World Soils Database (Nachtergaele et al., 2008);
- Observed planting and maturity dates and planting densities from the USDA crop progress reports released weekly during the growing season for many decades, generally at the resolution of states or CRDs (National Agricultural Statistics Service, 1995-2013),
- County-level data from 1979 to 2011 on irrigated and rainfed harvested areas from USDA NASS; and
- Estimates of sub-county distribution of land and management practices from the Spatial Production and Allocation Model (SPAM) dataset (You and Wood, 2006).

CERES-Maize does not include dynamic functions for pests, disease, or ozone damage. For nutrient stresses, we consider here only nitrogen stress and thus nitrogen fertilizers, ignoring phosphorus and potassium. Since maize in the US is almost uniformly grown with high levels of fertilizers, we do not expect that nutrient limitations are a large factor.

2.2. Aggregation, statistical correction, and validation

We aggregate raw simulation output to the county level and compare against survey data from USDA NASS (with linear trends removed) to correct statistical biases and estimate forecast errors. Despite the fact that we include time-varying technology and management factors that reproduce a significant portion of the trend in yields, the goal in considering these empirical and semi-empirical technology and

management changes explicitly in the modeling was to understand how they interact with system-level sensitivity to extreme drought and heat. Because we made no attempt to calibrate the time-varying technology parameters to explicitly reproduce yield trends, the simulated trends do not exactly reproduce the observed trends, thus a trend correction is still needed. The simulated yield in county *R* is thus

$$Y_R = (\sum_{x \in R} A_x^{rf} Y_x^{rf} + A_x^{ir} Y_x^{ir})/(\sum_{x \in R} A_x^{rf} + A_x^{ir}),$$

where A_x^{rf} and A_x^{ir} are the rainfed and irrigated area (resp.) in grid cell *x* according to SPAM, and Y_x^{rf} and Y_x^{ir} are the simulated rainfed and ir-rigated yield in gridcell *x*. The sum is over all grid cells in region *R*. Where time-varying areas are considered (for example in the counter-factuals), annual county-level data on irrigated and rainfed area is obtained from USDA NASS (thus, time-varying areas does not change the county level aggregate yield value but will change aggregate values at state and national level).

In each county for which observational yield data exist over at least 17 of the 33 years from 1979 to 2011, we estimate a multiplicative variance correction for each year as the ratio of the standard deviations of the observed and simulated values in all other years. This correction is necessary due to the fact that weather and other input datasets at the scales available are typically not able to capture the spatial variability and diversity of observed weather and management at the sub-county level (Dzotsi et al., 2013), leading to highly correlated yield values, and thus higher-than-observed variability, for the gridcells within a given county. Most limiting in this case is the use of 1/8th degree NARR historical climate data, chosen because it is the highest resolution da-taset that is released in near-real-time and contains all necessary vari-ables for driving crop models. For the 2012 estimates, this correction is calculated as the ratio of observed and simulated deviation for the 33 years from 1979 to 2011, without considering whether factors are changing over time or in drought vs. normal years. We compute a time-weighted additive bias correction for the yield in each (county, year) combination similarly, by calculating the average error in all other years for which data are available in the given county, weighted by the inverse-square of the time difference. In both cases we exclude the correction year from the estimated statistical weight with a leave-one-out methodology so as to avoid direct influence by the observed values on the simulated yield estimates.

2.3. Estimating long-term trend yield

Standard practice in comparing the performance of agricultural systems over time is to evaluate yield in each period relative to the "trend yield," a quantity that is defined in a number of ways and over a number of different periods with more-or-less equal validity. In its simplest formulation, trend yield at time T is defined as the value of the linear fit (at time T) of the observed yield data over some period T_1 to T_2. We define trend yield throughout this analysis as the linear fit to

observed yields at county, state, or national level from 1960 to 2011. We do not include 2012 because these simulations were performed before the official data for 2012 were released with the goal of fore-casting that official value. We start the fit in 1960 because there are major qualitative differences in the time-series before that year. We calculate an observed trend for each county in the USDA NASS survey for which data exist and project the statistically corrected simulated yields in each county against this trend. We aggregate the resulting estimates to state and national levels and compare them with survey data to characterize uncertainty across scales.

3. Results

3.1. Recent droughts

Hot and dry conditions in the US during the spring and summer of 2012 led to devastating crop losses in much of the country and the worst maize harvest in absolute terms since 1995 (the worst since 1988 relative to the increasing yield trend). A warm, dry winter ended early and abruptly with an extraordinary heat wave in March that left soils parched in much of the country. A hot, dry spring left crops stunted and fields wilted and brown toward the end of June. Sustained heat ac-celerated crop development stages, and extreme conditions in July (the hottest and second driest July on record since the drought of 1936) brought drought and heat stress to crops during key stages of devel-opment around flowering in much of the Corn Belt (Elmore, 2012). The spatial extent of drought peaked just after the maize harvest in Sep-tember, at which point over 65% of the conterminous US was experi-encing drought conditions according to the US Drought Monitor (Brewer and Love-Brotak, 2012), the largest spatial coverage of drought since the dustbowl of the 1930s.

The agricultural drought of 1988 is the only event of comparable severity to 2012 to have occurred in the US since the advent of high-quality satellite observations in the late 1970s. The total accumulated rainfall in May through September, averaged over maize area, was si-milar in the two seasons (33.0 cm in 1988 and 32.9 cm in 2012), but the rainfall deficit was most pronounced in May/June of 1988 and in June/July of 2012 (National Climatic Data Center, 2013). Temperatures were hot in both summers (June–August average temp was 23.7 °C in 1988 and 23.3 °C in 2012), but 1988 was consistently hot in all three months, whereas 2012 was extremely hot in July (average temperature of 26.3 °C) and only moderately hot in June and August.

While the Palmer Drought Severity Index (PDSI; National Climatic Data Center, 2013) is sensitive to meteorological and hydrological drought conditions, Palmer's Z-index (Dai, 2011; Karl, 1986) responds to short-term moisture anomalies and is a better predictor of crop yield impacts in recent decades (Fig. 1A). The Z-index indicates that in 1988, the most severe drought occurred from the Corn Belt to the northwest (Fig. 1B), while for 2012, it extended from the Corn Belt to the south-west (Fig. 1C).
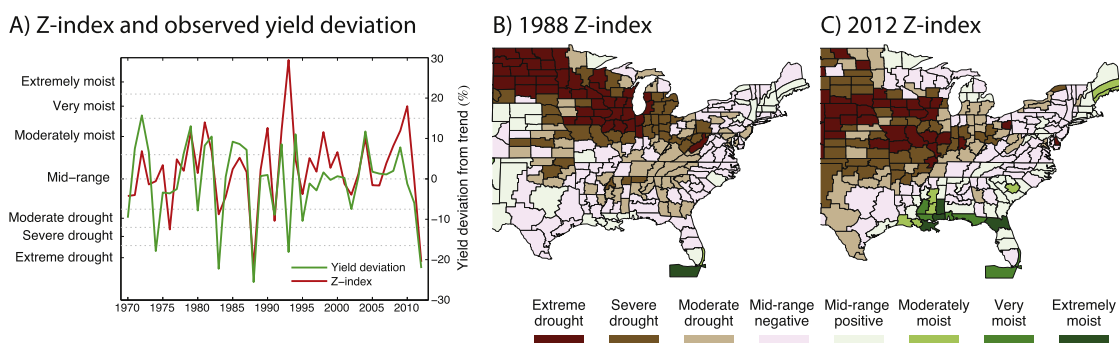

Fig. 1. A) Comparison between June-August average Z-index weighted by maize production over the US Corn Belt (left axis) and the observed deviation of average maize yield from trend (right axis); and the June–August Palmer Z-Index (by US climate division) for B) 1988 and (C) 2012.

Although the seasonal Z-index can highlight regions with likely drought impacts, further analysis of biophysical processes can elucidate the causes of lost yields. The sub-seasonal timing of the 1988 and 2012 droughts may have played a role in system-wide drought severity, because crops display increased sensitivity to temperature and drought stress during the key period around flowering, which can range from a single day to more than a week (Du Pisani, 1987; Eitzinger et al., 2004). According to USDA crop progress reports (National Agricultural Statistics Service, 1995-2013), which survey farmers in major agricultural states, the range of observed flowering dates (defined as the period between the days in which 15% and 85% of the total area was observed to be flowered) in 2008–2012 (July 1–22) was almost two weeks earlier than in 1980–1984 (July 13–August 1). Even so, the majority of the cornbelt still flowers in July and observed mean yields over 1979–2012 correlate most strongly with the Z-index over the production-weighted Corn Belt during this month (0.81 compared to 0.36 in June and 0.50 in August; excluding the 1993 flood year).

3.2. Modeling drought impacts to crops

In comparison to statistical models used alone, process-based models can improve predictability and provide deeper insight into the root causes of drought impacts. CERES-Maize in particular has a long history of drought-related applications around the world (Du Pisani, 1987; Eitzinger et al., 2004; Xie et al., 2001). In this study, we run CERES-Maize with weather data and management/technology trends from 1979 to 2012 to simulate location- and time-specific drought impacts. We derive technological trends independently of the model (i.e., without model tuning) from empirical and semi-empirical evidence (a combination of reported values from survey data and expert elicitation) as described in the Supplemental Material.

We aggregated simulated crop yields to the county level and corrected the measures for statistical biases and trends (compared against USDA NASS data at county level) to predict (retroactively) crop productivity in each county and year (see Methods for details). We then compared these estimates to USDA NASS survey-based yield observations to calculate the re-sampled forecast errors (shaded bands in Fig. 2 A and B) estimated with a leave-one-out cross-validation approach. Simulated national average yield for 2012 weather is 7.72 t/ha, 22% below trend. The interval based on the 75% range of resampled forecast errors (the darker bands in Fig. 2 A and 2B) stretches from 7.15 to 8.15 t/ha. Predicted 1988 yields are 25% below trend (5.39 t/ha), with a 75% range including resampled forecast errors of 4.81–5.82 t/ha.

On average over 1979–2012, median yield predictions deviate from NASS observations by 0.53 t/ha (6.7% of the sample mean). National average 2012 yield according to the official county-level USDA NASS statistics released in February 2013 was 7.75 t/ha, just 0.3% above our median estimate of 7.72 t/ha. The USDA also releases a national maize yield forecast each month from August–November(based on surveys of kernel counts and weights from fields around the country, as well as remote sensing and other data inputs) (The Statistical Methods Branch, 2012). In 2012, the final (November) USDA estimate of the national yield was 7.68 t/ha (the red dot in Fig. 2A).

The model also performed well in 1988, estimating national average yield 1.4% higher than the official national statistic of 5.31 t/ha (the November 1988 USDA yield forecast was 5.17 t/ha, 2.6% below the official value). However, our model significantly overpredicted yields in 1993, when excessive rainfall led to waterlogged soils throughout much of the Midwest causing root death and reduced growth (Rosenzweig et al., 2002). We have made no attempt to capture this effect here since we were primarily interested in the effects of heat and drought.

Drought damage in both 1988 and 2012 was fairly well distributed across the major US grain-producing regions, with the traditional cornbelt states hit hardest (Fig. 2 C and 2D). Local management factors dramatically affect drought tolerance among the states. Nebraska was near the epicenter of the 2012 drought, for example, with more

counties experiencing extreme drought conditions than neighboring states Iowa, Kansas, and Missouri (Fig. 2D). However, Nebraska was spared the worst consequences because 70% of maize in the state is irrigated in a typical year. The RMSE of the state-level yield estimates (Fig. 3 A and B) for the full sample is 1.14 t/ha. For the top 10 producing states (which together account for 79–86 % of maize production in the country each year), the RMSE is 0.85 t/ha (11% of the sample mean).

The model appears better able to reproduce observed yields in drought years than years with adequate rain. For the top five producing states, the RMSE is 0.76 t/ha (9% of the full sample mean), while in 1988 and 2012 the RMSEs are 0.49 and 0.55 t/ha (respectively). The model significantly underpredicts average yields in Nebraska in 1988 (by 1.09 t/ha or 14%) and Minnesota in 2012 (by 1.94 t/ha or 18.8%). These states were on the margin of the drought-afflicted regions in the respective years, but largely avoided extreme drought conditions. The model overpredicts average yields in Indiana in 2012 (by 0.84 t/ha or 14%), likely due to limited data for parameterization of key soil properties (overall depth and water-holding capacity).

3.3. System-level sensitivity and adaptation

Despite the fact that 1988 was comparable to (or even less severe than) 2012 by most climatic measures (e.g., the critical timing of drought peak in the Corn Belt), it had a significantly more pronounced negative impact on crop productivity and may have been more costly (NCDC, 2012; Riebsame et al., 1991). We hypothesize that this difference is due to changes in local land use (e.g. spatial distribution of cultivated land and prevalence of irrigation), technology (e.g. improved genetics in modern hybrid seeds), and management choices (e.g. earlier planting dates and higher planting densities) from 1988 to 2012 that have decreased the sensitivity of the US maize industry to large-scale drought.

To explore this hypothesis, we used CERES-Maize to test two historical counterfactual scenarios in which we swapped the observed weather from 1988 and 2012, so as to simulate the consequences of the 1988 drought if using 2012 management, and vice versa. Results indicate that the 2012 drought was notably more severe (Fig. 4). If weather in 1988 had matched the drought of 2012, average losses would have approached 2.1 t/ha (29.1% of trend). Similarly, if maize farmers in 2012 had experienced weather like 1988, losses relative to the trend would have been reduced to 1.8 t/ha (18.0% of trend). We conclude that changes in technology and management decisions since 1988 have reduced the sensitivity of the US maize industry to large-scale drought. Absent these changes, the severe agricultural drought of 2012 would have been even worse.

A corollary of this result is that assessments of the impact of extreme heat and drought that fail to consider changes in technology and management decisions may not accurately reflect system-level drought sensitivity. Indeed, had we not included parameterizations of time-varying management and technology drivers when forecasting 2012 maize productivity, we would have significantly underestimated average yields. This result has implications for near- and long-term assessments of climate impacts, adaptation, and food security.

3.4. The economic costs of drought and comparability

The economic loss implied by drought-induced declines in production is substantial. Overall US maize production in 2012 was about 274 million tonnes—an estimated 76 million tonnes less than trend due to drought-related productivity losses. At the average price received of $284/t, the harvest had a total value of $77.4 billion and weather-related revenue-loss of $21.6 billion. Reduced losses in the 2012 counterfactual scenario (1988 weather with 2012 technology and management) imply that for maize alone the 2012 drought was almost $4 billion dollars more costly (in 2012 dollars) than the 1988 drought.
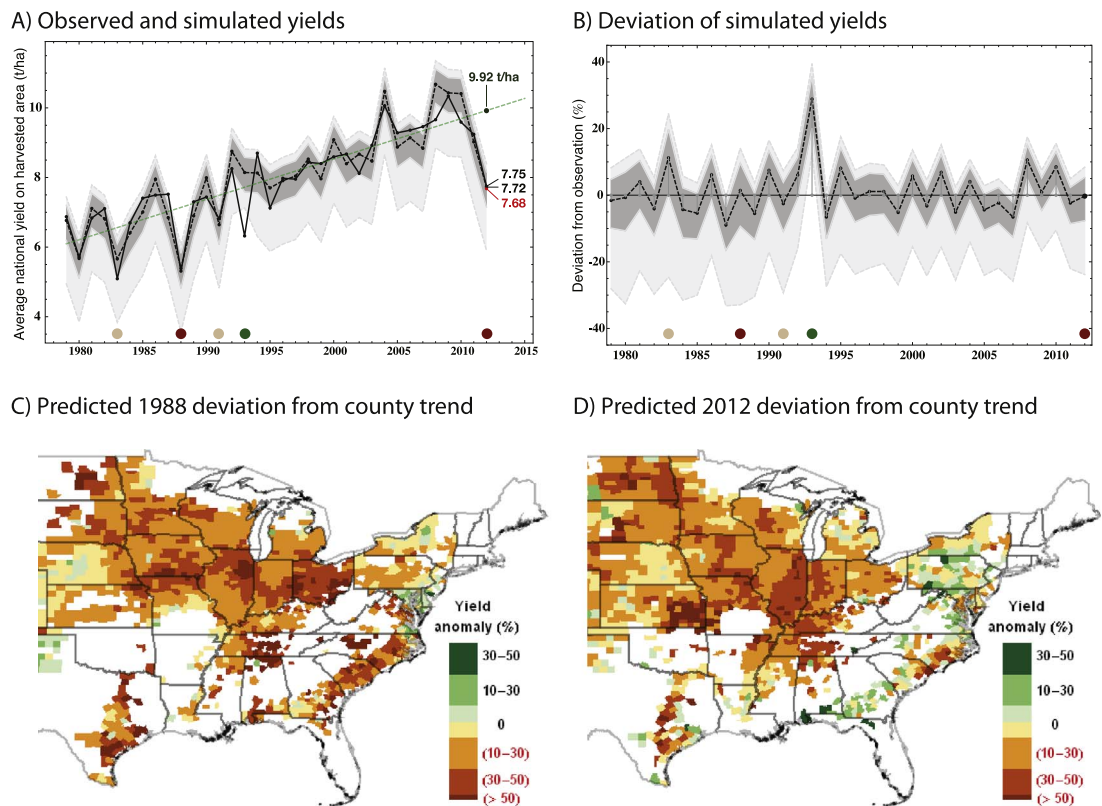
A) Observed and simulated yields

B) Deviation of simulated yields

C) Predicted 1988 deviation from county trend

D) Predicted 2012 deviation from county trend

Fig. 2. A) Predicted (dashed line and points), observed (solid line and points), and observed linear trend (dashed straight green line) of national average maize yield in tonnes per hectare from 1979–2012. The red dot indicates the USDA estimate for 2012 released in November 2012. We use shading to show the central 95% (lighter bands) and 75% (darker bands) of the resampled forecast error distribution (note that these bands tend to skew to the negative due to the significant miss high in 1993). The colored dots at the bottom of the panel denote years identified by the Z-index (in Fig. 1a) as being moderate-to-extreme drought years (1983, 1988, 1991, and 2012) or extremely moist (the 1993 flood). B) Deviation of the predicted national maize yield from observed, as a percent of the observation in each year. C) Median deviation of predicted county-level yields from linear trend for 1988 as a percentage of county-specific trend yield. D) Predicted deviation from trend for each county in 2012. Only counties with at least 500 ha of harvested maize area are shown.
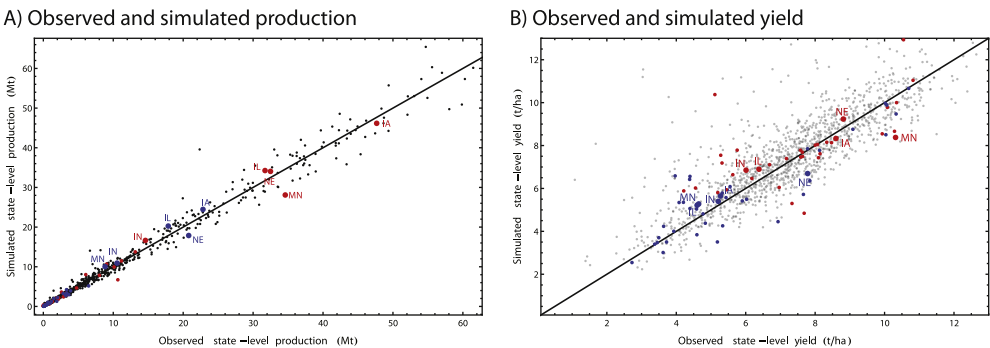
A) Observed and simulated production

B) Observed and simulated yield

Fig. 3. Scatterplots of state-level observed vs. predicted maize A) production (millions of tonnes) and B) yield (t/ha) for all (state,year) combinations with valid NASS data. 2012 states are highlighted in red and 1988 states in blue. The five largest producing states (Iowa, Minnesota, Nebraska, Illinois, and Indiana) are labeled explicitly.
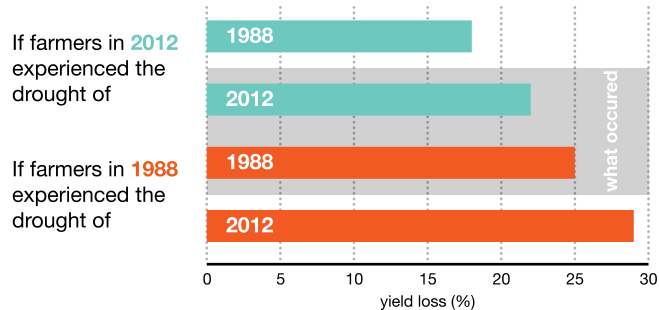

Fig. 4. Comparison of the productivity effects of drought over time by evaluation of the 1988 and 2012 droughts and historical counterfactuals.

Data from the USDA Risk Management Agency (RMA) Summary of Business (SOB) and Cause of Loss (COL) reports (USDA/RMA, 2012) provide an independent approach to estimating crop losses. According to RMA data, about $11 billion of indemnity payments were made to cover insured losses to 2012 US maize production (68% of the total indemnity for all crops), with 95% resulting from drought or heat stress claims (see Supplemental Information and Figs. S2–S6). To estimate total crop losses from drought in recent years, Smith and Katz (Smith and Katz, 2013) assume that about 70% of eligible areas are currently insured and that farmers choose to be insured at an average rate of about 70% of revenue—implying total lost farm revenue of about two times the total indemnity, or about $22 billion for maize. Using an expanded and more complete version of this method (summarized in the methods section and Supplemental Material Figs S2–S6), we estimate total drought loss for maize at each US county (Fig. 5A).

Estimates of losses at the county level match closely with

A) 2012 total maize lossses (RMA)   B) 2012 total maize lossses (simulated)   C) 1988 total maize lossses (simulated)
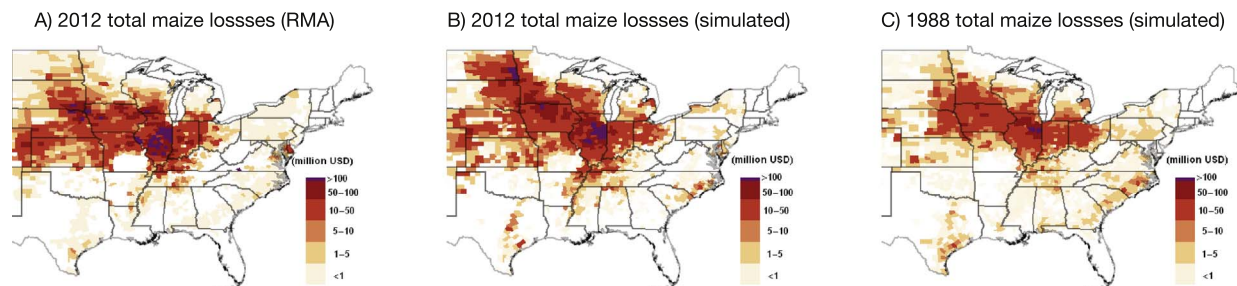

Fig. 5. (A) 2012 drought/heat related losses for commercial maize, estimated from USDA RMA indemnity data. B) Estimated county-level losses according to simulated productivity effects of the drought. C) Simulated crop losses for commercial maize during the 1988 drought, adjusted for inflation to 2012.

predictions generated from simulations (Fig. 5B). This result suggests that we can use a model-based simulation method to estimate losses in other regions or time-periods for which detailed records are not available. For example, maize production in 1988 totaled 125 million tonnes with estimated losses due to reduced productivity of ~46 million tonnes. At the average price received of $101/tonne ($195 adjusted to 2012) the harvest had a total value of $12.7 billion ($24.6 billion adjusted), and weather-related lost farm revenue (adjusted for inflation) of almost $9 billion. Insurance coverage in 1988 was much less common than in 2012, with indemnity payments for drought and heat events totaling only $928 million for all crops. It is therefore not possible to use a methodology based on RMA data to generate consistent cost estimates at any scale for 1988, making existing analyses (NCDC, 2012; Riebsame et al., 1991; Smith and Katz, 2013) not directly comparable with 2012.

Our model-based approach enables unbiased comparisons of drought damages and costs that can be used to compare the economic costs of extreme events with various assumptions and at various scales. Increased losses in the 1988 counterfactual scenario imply an additional cost of about $1 billion if farmers in 1988 had instead experienced 2012 weather. Evaluated at the county level, losses from the 2012 drought were more widespread and generally larger than the 1988 drought (Fig. 5 B and 5C). The financial impacts of the 2012 drought to the US commercial maize industry as a whole were 25% more severe than in the 2012 counterfactual, and the costs of the 1988 drought were 10% less severe than in the 1988 counterfactual.

4. Conclusions

The challenge of drought is a global reality that affects agriculture in both the developed and developing world and is expected to worsen as climate change proceeds. We show that process-based crop models applied at large scales are able to reproduce the effects of drought events in the historical record with good accuracy in the US. Calibrating models for use in developing countries is often challenging due to a lack good district-level yield data like that available in the US case. In addition, soils are often poor and fertilizer use is highly heterogeneous and generally not known, making it much more difficult to implement models at high-resolution over large areas. A comprehensive approach to monitoring, modeling, and predicting growing seasons globally, using the novel approaches applied here in the context of the US, could provide actionable local information within a global context. This would improve the basis for decision-making on seasonal timescales and beyond and would reduce the risks associated with droughts and other climate extremes by improving lead times for interventions. Recent work has found that statistical yield models applied similarly have some ability to predict crop losses as well, but with some restrictions in the areas of applicability (Iizumi et al., 2013). The value of large-scale process-based models for prediction, monitoring, and evaluation will be further enhanced by improvements in the accuracy and fidelity of seasonal temperature and precipitation forecasts with lead times of several weeks or months. Improvements to model process

representations and assessment techniques, such as those pursued within the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig et al., 2013), will also improve forecast capacity.

Our results indicate that the relative impacts of historical droughts on food production cannot be accurately characterized without considering technology and management changes and their interaction with weather and extremes. Beyond the implications for predicting and understanding the effects of historical and emerging extreme events, this result poses challenges to the statistical methods by which some future global change scenarios for agriculture are constructed (Müller and Robertson, 2014). These methods typically assume that technology change and climate impacts satisfy an approximate separability condition and that realistic future scenarios can be generated by estimating each independently and superimposing the results. We find that this assumption may not hold for even recent historical timescales (24 years in this case).

The approach contributes new methods for estimating the severity and financial costs of agricultural drought, which often depend on unreliable and/or inconsistent sources. It also allows for an unbiased comparison of severe events occurring decades apart and under different conditions. These features may make the tools useful for agricultural insurance and reinsurance applications in the developing world. The observational yield data necessary to price risk in these markets is often unavailable, of insufficient quality, or is too difficult to evaluate because strong and unpredictable trends or non-climatic factors such as political upheaval. High-resolution simulations in these cases are often hampered by lack of quality climate, soil, and management data, but may still be "better than nothing."

These results also suggest that monitoring, modeling, and analysis tools can help improve farm management by considering historical trends in technology and practices and evaluating their effects on drought sensitivity. We show that technology and practices have reduced the system-level sensitivity to drought in the US. Our methods may also allow for evaluation of the benefits of deploying similar technology and practices in other regions. For example, it may be possible to improve drought tolerance through changes in farming methods from field- to system-level scales. Potential adaptation strategies include increased investment in drought-tolerant varieties, expanded and efficient irrigation technologies that leverage sustainable water resources and minimize ground water depletion (Elliott et al., 2014a), low-till and no-till farming, and improved soil water retention through cover crops and smart fallow management (Hatfield et al., 2001). Probabilistic forecasts using approaches such as those described here could play a significant role in evaluating the benefits and/or tradeoffs of such crop-risk management practices, thereby reducing losses and increasing returns.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.agsy.2017.07.012.

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